Prior Workload has Moderate Effects on High-Intensity Match Performance in Elite-Level Professional Football Players when Controlling for Situational and Contextual Variables.

Original Investigation.

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Title

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Running Title

Effect of Prior Workload on High-Intensity Match Performance in Football.

Abstract

This investigation examined the effect of prior workload on high-intensity football match performance. Player load variables were recorded using a global positioning system and converted into composite variables: rolling season accumulated load (AL), exponentially weighted moving average acute, chronic and acute:chronic workload ratio (A:C). Match-play high-intensity performance-per-minute: accelerations (ACC), sprints, high-speed running (HSR) and high metabolic load (HMLd) distances; and situational and contextual variables were recorded for all games. Partial least squares modelling, and backward stepwise selection determined the most parsimonious model for each performance variable. Quadratic relationships of *small* to *moderate* effect sizes were identified for sprint AL and sprint performance, HSR AL and HSR performance, acute HMLd and HMLd performance, acute sprint load and ACC performance and A:C sprint load and ACC performance. Match performance was typically greatest between the mean and +1SD. High chronic HMLd, and combined acceleration and deceleration (ACC+DEC) load exerted *small* beneficial effects on HMLd and HSR performance, whereas high acute load exerted *trivial* to *moderate* negative effects. High sprint A:C exerted a *small* beneficial effect on sprint performance and playing position exerted *small* effects on HSR and HMLd performance. Prior workload has *trivial* to *moderate* effects on high-intensity match performance in professional players.

Keywords

Acute; Chronic; Workload; Fatigue; Performance; Monitoring.

Introduction

'Load' in professional Association Football (football) describes the cumulative physiological and psychological stress applied to a player from training and match play over time [1-3]. Accordingly, 'load management' is the process of controlling external load (the work completed by the player) to mitigate the player's internal (physiological) response. The incorporation of load management in football attempts to improve player 'readiness' (to accept new load) by optimising 'fitness' and dissipating 'fatigue' around games. Since readiness is associated with physical performance potential, injury and illness risk [1-5], effective player load management is critically important in football.

In practice, load management is supported by the implementation of Global Positioning (GPS), micro electrical mechanical (MEMS), and / or in-stadia computerised tracking (CT) systems. These provide a wealth of data in the form of load monitoring variables to describe the volume and intensity of training and match play. Load variables are typically converted into composite values to reflect 'acute' (~ 7 d average load; analogous to player 'fatigue') and 'chronic' (~ 28 d average load; analogous to player 'fitness') load and the acute : chronic (A:C) workload ratio

[6] to describe recent patterns in the distribution of load. Accordingly, a large number of workload indices are available to practitioners, creating a complex decision-making matrix, which is often challenging to interpret [7].

There is a paucity of data available to describe the workload-performance relationship at the professional level of elite football. A number of studies have reported an equivocal effect of increased fixture density *per se* on match play physical performance [8-13]. However, there are no studies available to report how specific measures of prior player load interact with subsequent measures of match play physical performance. Since load is known to correlate with player fatigue status [14] and modulate player recovery kinetics [15], it seems reasonable to hypothesise that prior load will influence subsequent match play physical performance.

Analysis of player load data is challenging owing to the small sample size of teams and the problem of multicollinearity that often exists between load variables [7]. Multicollinearity is particularly problematic in data derived from GPS, MEMS and CT technology [16], and needs to be controlled to avoid erroneous conclusions [7]. Recently, Weaving and colleagues (2019) demonstrated merit in the use of the partial least squares correlation analysis (PLSCA) technique to overcome these problems. This successfully identified predictor variables for 'fitness' development in professional rugby players from training load indices alone [7]. Accordingly, this method might add value to other analyses of performance data.

Situational and contextual variables (i.e. match location, match outcome, quality of opposition, fixture density and match goal deficit) can exert an influence on match play physical performance [17,18]. Accordingly, where possible, these should be included as covariates in statistical models designed to determine the contributing factors of match play physical performance [17]. Despite the influence that prior load might exert on match play physical performance in football; a comprehensive analysis of the effect of prior load on match play physical performance is yet to be completed. Match play high-intensity and high-speed running performance variables are of particular interest since they are strongly related to player training status [19,20], can have a decisive role during match play [21,22] and can partly contribute to match outcome [23]. At present, however, practitioners lack clarity regarding the load quantification variables, both absolute and composite measures, that best relate to match play high-intensity and high speed-running performance. As such, their contributing factors warrant further investigation. Accordingly, the aim of this study was to investigate the effect that prior load has on high-intensity and high-speed running match play physical performance in elite-level professional football players. This was achieved using a PLSCA method to identify the strongest predictor variables of match play physical performance, including situational and contextual variables as covariates.

Methods

Study design

Daily training load and match play physical performance indices were recorded in 18 senior professional male outfield players (age = 24 ± 4 years; height = 181 ± 7.0 cm, body mass = 72.4 ± 5.2 kg) from one English Championship team across a complete competitive season. Of these players, 3 were central defenders, 4 were wide defenders, 4 were central midfielders, 4 were wide midfielders and 3 were forwards. The season consisted of 48 competitive fixtures (46 league and 2 domestic cup games). An ethics declaration was approved for this investigation by the Edith Cowan University (AU) Human Research Ethics Office.

Training load

Player training load was recorded for all training sessions across the pre-season and in-season phases. External load was measured using GPS and MEMS sensors (Statsports Viper 2, Belfast, Northern Ireland, UK), sampling at 10 Hz (GPS) and 100 Hz (tri-axial accelerometer, gyroscope and magnetometer). These devices are valid and reliable for the measurement of distance and instantaneous low-speed (jogging) and peak-speed running during multidirectional and linear running activities that replicate the demands of football [24]. Typical error for distance and instantaneous speed are reported as < 3% (*good*) and < 2% (*good*) [24] respectively. A software application (www.gnssplanning.com) [25], was used to identify a geographical point (ground station) based on the latitude and longitude coordinates of the team training facility. This determined the mean number of satellites and horizontal dilution of precision for GPS data across the sample period, which equated to 8.7 ± 1.0 and 0.66 ± 0.08 % respectively. This is in accordance with studies evaluating football demands using GPS systems [26] and indicates optimal conditions for satellite transmissions [27].

Players wore the same GPS device for all training sessions. Devices were worn in a neoprene vest, positioned between the scapulae as per manufacturer guidelines. Player total distance (TD) – (total distance completed (m)); high-speed running distance (HSR) – (total distance completed between 5.5 m/s and 80% of individualised maximal linear running velocity (m)); high metabolic load distance (HMLd) – (distance covered when energy consumption per kilogram per second is > $25W/kg^{-1}$ (m)); number of sprints (total number of sprint efforts > 80% of individualised maximal linear running velocity); and high intensity variables: total number of accelerations (ACC), decelerations (DEC) and changes to speed (ACC+DEC) were recorded. ACC and DEC efforts were identified according to the manufacturer's guidelines, as a change in player velocity of > 0.5 m/s^2 maintained for > 0.5 s. Efforts were zone-banded based on the peak magnitude of ACC or DEC with thresholds set at > 3 m/s^2 and > -3 m/s^2

respectively. These thresholds are consistent with those used in previous research literature [28-33] and have demonstrated sensitivity to match related fatigue in professional football players [29,30]. Training load data were extracted from GPS devices using manufacturer software (Statsports Viper, Belfast, Northern Ireland, UK). The authors did not extract any raw GPS data or apply filtering processes. Internal load was calculated using session rating of perceived exertion (sRPE) – (sRPE rating [34] multiplied by session duration (mins) (A.U.)). Session RPE data were collected within 30 min of the cessation of training. Variable selection was based on popularity of use in practice in professional football [6]. All training load data collection and analysis was completed by the same investigator across the sample period. Typical workload distribution during single and double game week microcycles across the sample period are presented in Figure 1, below.

****Insert Figure 1 Here****

Match load

Player match load was recorded for all competitive home and away games across the season. External load variables were measured using 6 fixed semi-automated high definition motion cameras in-stadia (Chyronhego TRACKAB, London, UK). Following games, raw TRACKAB player position data were converted to equivalent training load variables using the manufacturer software (Statsports Viper, Belfast, Northern Ireland, UK). This method has been described previously [35], and is widely used in practice and research [4]. Published data from elite-level professional football match play indicate strong relationships between Statsports Viper and TRACKAB for TD (r^2 = 0.98) and HSR (r^2 = 0.98) [35]. Our unpublished data from elite-level professional football match play indicate a strong relationship for HMLd (r^2 = 0.93), ACC (r^2 = 0.94), DEC (r^2 = 0.95) and number of sprints (r2 = 0.97) using this method.

Workload indices

Training and match load data were summated to establish total player workload indices across the season. For each load variable, 7 d absolute sum, 28 d absolute sum, rolling season absolute accumulated load (AL), exponentially weighted moving average (EWMA) acute load, EWMA chronic load and the EWMA acute : chronic workload ratio (A:C) were calculated. The EWMA method accounts for the decaying nature of fitness and fatigue effects over time and is a more sensitive method for assessing training load than the rolling average method [36] that has been used previously [4,5]. EWMA indices were calculated using equations by Williams and colleagues [36]:

$$EWMA_{today} = Load_{today} * \lambda_a + ((1 - \lambda_a) * EMWA_{yesterday})$$

Where λ_a represents the degree of time decay. Time decay was calculated using:

$$\lambda_a = 2/(N + 1)$$

Where *N* is the chosen time decay constant. Decay factors representing time constants for 7 d (acute) and 28 d (chronic) were used. These equated to 0.25 and 0.069 respectively.

Match play physical performance

Four high-intensity and high-speed running match play physical performance variables were selected for analysis. Variable selection was based on current practice in professional football [6]. Selected variables were ACC / min, sprints / min, HSR m / min and HMLd m / min. Match play physical performance was calculated by dividing performance by match duration to provide a performance-per-minute value for each variable. Games in which players played less than 75 min were excluded from the analysis. There were no games in which 'extra time' was played.

Data from 7 games in which a player was sent-off from either the sample team or their opposition were omitted from the analysis. Data from a further 3 games were omitted owing to technical error. In cases where players were injured, ill or required to train or play games for national teams, 7 d and 28 d workload - match interactions were omitted from the analysis until a 28 d period of full training for the reference team had been completed. For national team players, all AL data were omitted from the analysis owing to missing workload data from national team duty. Following these exclusions, data from 38 games (353 player match observations) and 4041 player training observations were included in the analysis.

Situational and contextual variables

The phase of the competitive season (season quarter (Q) 1, Q2, Q3 or Q4), current fixture density (number of games in the last 7 d), match location (home or away), match outcome (win, draw or loss), match goal deficit (positive value for a win, negative value for a loss) and quality of opposition were recorded for each match observation. To determine quality of opposition, teams were divided into high (top third, positions 1 - 8), intermediate (middle third, positions 9 - 16) or low (bottom third, positions 17 - 24) groups based on end of season league position.

Team Performance

For context, the reference team finished the season in 9th (out of 24 teams) position in the league ('middle' league quality group): winning 19 games, drawing 8 games and losing 19 games. Season mean (± SD) goal deficit across the season was -0.01 ± 1.9.

Statistical analysis

All statistical analysis was conducted using *R* (version 3.5.1, R Foundation for Statistical Computing, Vienna, Austria). A two-stage data reduction process was used to determine the most parsimonious model for each high-intensity and high-speed running match play physical performance variable.

The 'multivariate methods with unbiased variable selection ('*MUVR'*) algorithm for multivariate modelling [37] was used to identify the minimal-optimal candidate predictor variables for each of the selected match play physical performance variables. The MUVR package is an algorithm for multivariate modelling, aimed at finding associations between predictor data (an X matrix) and a response (a Y vector) via partial least squares modelling. MUVR is useful for handling data that has large numbers of variables and few observations, and constructs robust, parsimonious multivariate models that generalize well, minimize overfitting and facilitate interpretation of results [37].

The candidate predictor variables identified for each match play physical performance measure were entered into a backward stepwise selection procedure to identify the best-fitting overall model [38]. Quadratic polynomials and interaction effects between predictors were considered as part of this process. Player identity was included as a random effect to account for repeated observations within players. Effects were deemed to be statistically significant at an alpha level of $P < 0.05$. Data are presented as means and 95% confidence intervals (CI), alongside Cohen's *d* effect sizes (ES) [39]. Thresholds for ES were: 0.0-0.2 = *Trivial*; 0.2-0.6 = *Small*; 0.6-1.2 = *Moderate*; 1.2-2 = *Large*; >2 = *Very Large*.

Results

Team Match Play Physical Performance

Team average match play physical performance data are provided in Table 1.

****Insert Table 1 Here****

Load Variables Relating to Match Play Physical Performance

Twenty load variables related to performance: AL, acute, chronic and A:C for: sprints, ACC+DEC, HSR, HMLd and sRPE (Table 2).

****Insert Table 2 Here****

Predictors of Match Play Physical Performance

Sprint performance

Only sprint AL load was retained from the variable selection process (Table 3). A quadratic effect was identified for this relationship (P = 0.002; ES = *Small*) (Figure 2); performance was generally highest near the mean or ~1 SD above the mean for season accumulated load.

****Insert Table 3 Here****

****Insert Figure 2 Here****

HMLd Performance

Five variables were retained from the variable selection process (Table 4): playing position (using CD as the reference group): WM (P = 0.008; ES = *Small* ↑), CM (P = 0.133, ES = *Small* ↑), F (P = 0.176, ES = *Small* ↑), WD (P = 0.134, ES = *Small* ↑); acute HMLd (P = 0.012, ES = *Moderate* ↓); chronic HMLd (P = 0.001; ES = *Small* ↑) and chronic sRPE (P = 0.042; ES = *Trivial* ↓). A quadratic effect was identified for acute HMLd (P = 0.012; ES = *Moderate*) (Figure 3), with HMLd performance generally highest at 2SDs above the mean value for acute HMLd.

****Insert Table 4 Here****

****Insert Figure 3 Here****

HSR Performance

Five variables were retained from the variable selection process (Table 5): playing position: CM (P = 0.146, ES = *Small* ↑); F (P = 0.068, ES = *Small* ↑); WD (P = 0.037, ES = *Small* ↑); WM (P = 0.001, ES = *Small* ↑); HSR AL (P = <0.001, ES = *Moderate* ↑); chronic ACC+DEC (P = 0.008, ES = *Small* ↑) and acute HMLd (P = 0.550, ES = *Trivial* ↓). A quadratic effect was identified for HSR AL (P = 0.002, ES = *Small*) (Figure 4), with HSR performance generally highest near the mean or ~1 SD above the mean for season accumulated HSR load.

****Insert Table 5 Here****

****Insert Figure 4 Here****

ACC Performance

Five variables were retained from the variable selection process (Table 6): acute sprints (P = 0.074 ES = *Small* ↑); A:C sprints (P = 0.083; ES = *Small* ↓) and goal deficit (P = 0.004; ES = *Trivial* ↓). Quadratic relationships were identified for acute sprints (P = 0.042; ES = *Small*) (Figure 5) and A:C sprints (P = 0.003; ES = *Small*) (Figure 6), with performance values generally highest at higher levels of these load measures.

****Insert Table 6 Here****

****Insert Figure 5 Here****

****Insert Figure 6 Here****

Discussion

The aim of this study was to investigate the effect that prior load and situational and contextual variables had on high-intensity and high-speed running match performance in professional football players. Four performance variables were selected: ACC/min, sprints/min, HSR m/min and HMLd m/min and the most parsimonious predictive model for each was determined. Workload indices were identified as predictor variables for all performance variables, exerting trivial to moderate effects, indicating that prior workload influences high-intensity and high-speed running match play physical performance in professional players. To the authors knowledge, this is the first investigation to report the effect of prior workload on match play physical performance in elite level professional football players.

Importantly, the physical demands of match play reported in the current investigation are similar to other data reported from the English Championship [40,41]. For example, the season team average total and high-speed running distances reported herein were 10,604 ± 1180 m, and 752 ± 237 m respectively (Table 1), which are similar to data reported by Bradley et al [40]; (11,429 ± 816 m and 803 ± 227 m) and Di Salvo et al [41]; (11,102 ± 916 m and 750 ± 222 m). Accordingly, it is apparent that match demands in the current investigation are representative of typical match demands in the English Championship.

The most important result from this investigation was the quadratic relationship identified between sprint AL and match play sprint performance; indicating that excessively 'high' and 'low' sprint AL might have compromising effects on match play sprint performance (Figure 2). Athletic performance potential is considered a product of the positive (fitness) and negative (fatigue) responses to workload [42]. Accordingly, our finding might reflect the influence that these factors have on match play physical performance. Further support for this notion is provided by the quadratic relationship also observed between HSR AL and HSR performance (Figure 4), in which excessively low and high values were associated with compromising effects. Collectively, this indicates that excessively low or high sprint and HSR AL workloads might compromise match play sprint and HSR performance. Excessive loading is known to induce player fatigue, non-functional overreaching and compromise player readiness to perform [1-3]. Conversely, excessively low loading will likely limit the adaptive responses to training, compromise physical development and reduce capacity to perform high sprint and HSR loads during match play [1-3].

The quadratic relationships between sprint AL and sprint performance (Figure 2) and HSR AL and HSR performance (Figure 4) infer an optimal 'zone' for player load exposure. For example, optimal match play sprint and HSR performances were achieved at approximately squad mean sprint, (Figure 2) and HSR (Figure 4) AL, with lesser performances observed around these values. Interestingly, a similar workload-performance relationship has been reported previously. Lazarus et al. [43] demonstrated optimal match performances when workload indices were within 1 SD of the squad mean in Australian Football Players (AFL). Collectively these data indicate the need to both adjust player training load according to match participation and ensure sufficient exposure to sprint and HSR load for players with limited game exposure.

Interestingly, we also found that recently acquired sprint workload influenced match play ACC performance (Table 6). We observed non-linear relationships between acute sprint load and ACC performance (Figure 5) and between A:C sprint load and match play ACC performance (Figure 6). Indicating that exceptionally low and high acute sprint workloads can exert a small compromising effect on match play ACC performance. Our finding that exceptionally low acute sprint workloads reduce match play ACC performance might illustrate the importance of player 'fitness' in determining match play physical performance potential. That is, a minimal amount of sprint load is required to support high-intensity match performance [1-3]. Our finding that excessively high acute sprint loads compromise match play ACC performance (Figure 5) is most likely a consequence of fatigue [1-3]. Since sprinting is considered a dominant causal activity of neuromuscular fatigue [44], it is plausible that high sprint workloads in close proximity to games, compromise match play ACC performance.

Another interesting finding from this investigation is the small linear relationship identified between chronic HMLd load and match play HMLd performance (Table 4). Specifically, our result is that high chronic HMLd load improves match play HMLd performance. HMLd is considered a 'global' measure of high-intensity performance; accounting for acceleration, deceleration, sprinting and HSR activity (in any combination). Therefore, our result indicates that a high chronic exposure to high-intensity activity *per se* can result in an increase in match play high-intensity actions. Since HMLd is widely used in practice [6], this result is likely to be of practical importance. Our result is consistent with other recent data that has associated high chronic workload indices with improved player performance. Recently, Hulin and colleagues [45] reported a *near perfect* (R^2 = 0.91) relationship between chronic workload and maximal running performance in Rugby League players. In addition, several other studies have demonstrated that high chronic workloads improve readiness in professional football players [4,5,46], as indicated by a reduction in injury risk. Typically these findings are attributed to advanced physical qualities obtained from high chronic workloads [42]. Indeed, our data indicate that a high chronic HMLd load might drive physiological and performance adaptations, which improve subsequent match play HMLd performances.

Interestingly, acute HMLd workload shared a quadratic relationship with match play HMLd performance (Table 4). This demonstrates that exceptionally low and high acute HMLd workloads might result in superior match play HMLd performances compared to moderate workloads (Figure 3). Of note, periods of short term (~ 7 – 14 d) reductions in workload are known to improve physical performance in athletes [47]. Likely, as a result of the dissipation of fatigue and the supercompensation achieved from preceding phases of training and competition [47]. Accordingly, the beneficial effect of exceptionally low acute HMLd workloads observed herein might be explained by a tapering effect in certain microcycles which improved subsequent match play HMLd performance.

Our finding that high acute HMLd workloads improved match play HMLd performance (Figure 3) is somewhat surprising. Excessive acute HMLd workloads are known to compromise stress balance in professional players, as indicated by increases in salivary cortisol when HMLd workloads are high [48]. Other researchers have reported that high acute workloads compromise physical performance in elite rugby players [45], and reduce readiness in football players [3-5,46]. This is likely a consequence of fatigue or non-functional overreaching [1-3]. As such, in the absence of a logical mechanistic explanation, we speculate that this result might be an artefact of the 7 d decay factor used to calculate acute workload in the present study. In some microcycles it is possible that an exceptionally high HMLd load is accrued 'early' in the training week (~ match day -5, -4 and -3) and an exceptionally low HMLd load was accrued immediately preceding match play (~ match day -2 and -1). Indeed, it was typical for the reference team to substantially reduce training load in the two days preceding match day (match day -2 and -1; Figure 1); consistent with football 'tapering' strategies that have been observed elsewhere in the research literature [49-51]. Similar to previous observations [49-51], lower intensity and volume 'tactical' orientated football training sessions were typically delivered on the days immediately preceding match day (i.e. MD-1 and MD-2; Figure 1); and higher intensity and volume 'physical' orientated football training sessions were typically delivered at the beginning of the microcycle (i.e. MD-4, Figure 1). This scenario might give rise to a 'high' 7 d load but still provide sufficient time for recovery prior to match play, such that match performance is not compromised. Alternatively, since relatively few observations were made at ~ 2 SD, these data might simply reflect unique responses in some players.

Interestingly, though acute and chronic HMLd load variables were identified as predictor variables for match play HMLd performance (Table 4), HMLd A:C load was not selected. To determine match play HMLd performance potential, our finding indicates merit in the use of uncoupled (A, C) as opposed to coupled (A:C) acute and chronic load monitoring. This is in contrast to previous work in cricket, which demonstrated a strong relationship (R^2 = 0.99) between coupled and uncoupled workload methods, and an equal capacity for either to determine relative injury risk [52]. However, our result is consistent with other recent work in professional football, which report merit in the uncoupled method, albeit for injury prediction [53]. Accordingly, it appears that the sport differentiates the required monitoring method, with current evidence at least, supporting the use of the uncoupled method in football.

Of the situational and contextual variables analysed, only playing position (for match play HMLd and HSR performance, Tables 5 and 6) and goal deficit (for ACC performance, Table 6) were identified as predictors. High-intensity and high-speed running demands of match play are on average, greater for WD, WM and CM than CD and F [40]. Therefore, it is not surprising that match play HMLd (Table 4) and HSR (Table 5) performances were greater in these positions. Moreover, since players are reported to perform more high-intensity activity during small, as opposed to large, goal deficits [18] our finding that goal deficit was a predictor for ACC performance is also unsurprising. However, the absence of quality of opposition as a predictor variable for match play physical performance is somewhat surprising, as players are reported to complete more high-intensity activity and high-speed running when playing against high- as opposed to low- quality opposition [54]. This finding might reflect a more homogenous nature of quality of opposition in the English Championship; in comparison to other top European leagues.

Practical Applications

Sprint and HSR AL variables should form an integral part of the player monitoring process. Our finding indicates that sprint and HSR load should be increased or decreased in cases of excessively low and high values to keep players in an optimal zone of preparation for performance. This finding supports the utilisation of maximal velocity running sessions, which have recently gained popularity in contemporary training programmes; particularly for squad players lacking in game exposure.

Practitioners should consider a linear physical development model for sprint and HSR during the preseason period and a concurrent physical development model during the in-season period. Players should be exposed to moderate to high loads across preseason (to develop ‘fitness’) but, where possible, maintain consistent (moderate) load exposure across the in-season phase, to mitigate the risk of ‘fatigue’. This distribution pattern might help to soften the inverted-U relationship observed in our data (Figures 2 and 4).

Players should develop a high chronic HMLd load. HMLd is a global measure of high-intensity activity and we observed a small linear relationship between chronic HMLd exposure and match play HMLd performance (Table 4).

Professional leagues should consider the performance consequences of scheduling games at high densities. English Championship teams are known to regularly play four games in 12 days or two games in three days during traditional periods. Since high acute loads generally exerted negative effects on match performance, high fixture densities will likely have negative implications on the performance level of players owing to limited recovery time.

We defined a sprint as an effort > 80% of individualised maximal linear running velocity. Of note, the average maximal velocity for the cohort herein was 9.4 ± 0.2 m/s, equating to an average velocity at 80% of maximal speed of 7.5 ± 0.2 m/s. Accordingly, the individualised sprint threshold was 0.5 m/s (~7%) higher than the absolute (7 m/s) threshold widely used in other football literature [4,40]. Since the threshold herein was predictive of match play sprint performance (Figure 2), we propose that there is merit in individualising speed workload monitoring thresholds to 80% of individualised maximal linear speed.

Limitations

The role of high-intensity activity in football match play is complex. For example, previous data indicates strong relationships between match play high-intensity performance and training status [19,20]. However, other data indicate that highly successful teams might complete less high-intensity activity during match play by virtue of being technically and / or tactically superior [55], not necessarily owing to being less 'fit' or more 'fatigued' *per se*. Indeed, the authors acknowledge that a combination of player fitness, fatigue, pacing strategies [56], motivation and other situational and contextual variables might influence match play high-intensity performance. In addition, we acknowledge that there are a lack of supporting validity and reliability data available for measuring HMLd, HSR and number of sprints, ACC and DEC efforts using the GPS device employed herein. Though these metrics are widely used in practice, we acknowledge that this is a substantial limitation of the current investigation. Finally, this investigation reported number of sprint efforts and the authors acknowledge that sprint distance is an alternate measure of sprint performance that might also be of practical interest.

Conclusion

Prior workload can have trivial to moderate effects on high-intensity match performance in professional football players.

Disclosure Statement

The authors report no conflict of interest.

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Tables and Figures

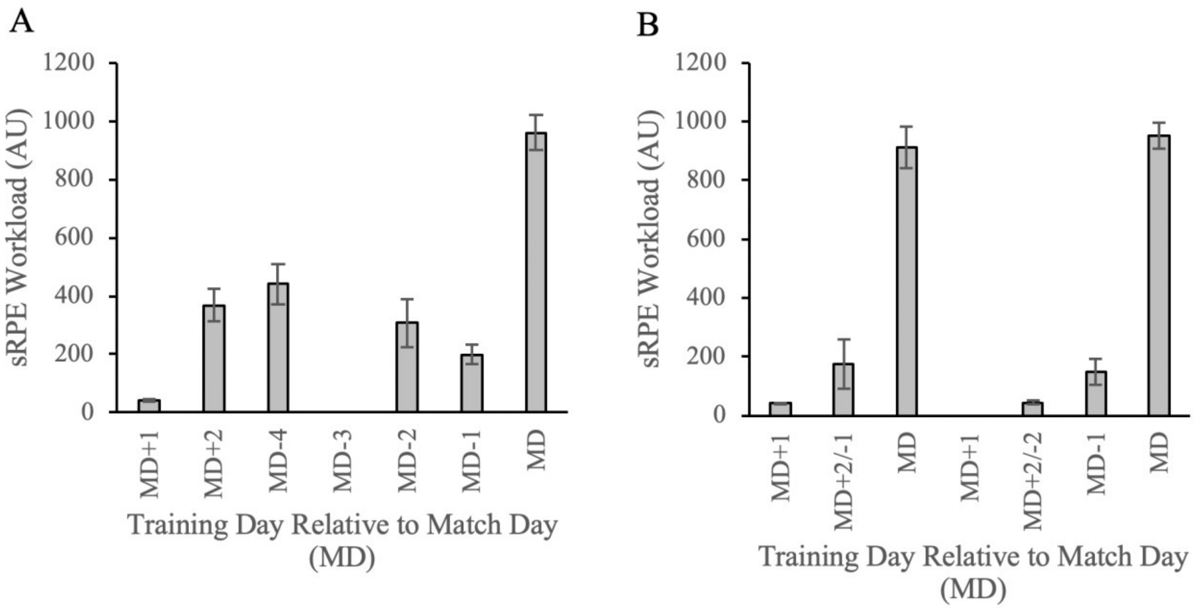

Figure 1. Typical workload distribution during A) Single-game weeks and B) Double game weeks across the sample period. Player days 'off' were allocated on MD-3 (single game weeks) and MD+1 following game one during double game weeks. MD+1 and MD+2/-2 sessions constituted 'off-feet' recovery sessions.

Table 1. Descriptive data for match-play physical performance parameters across the sample period in the reference team. Data are presented as mean ± SD with 95% CI.

Match Performance Variable	Mean ± SD	CI
Accelerations (number)	101 (25.6)	95.8 - 108
Decelerations (number)	112 (28.5)	109 - 115
Accelerations + Decelerations (number)	213 (51.9)	207 - 219
Sprints (number)	8.8 (3.8)	8.39 – 9.21
High-Speed Running (m)	752 (237.1)	726 - 778
High Metabolic Load Distance (m)	2159 (387.1)	2120 - 2200
Total Distance (m)	10604 (1180)	10500 - 10700

Table 2. Minimal-optimal number of predictor variables for each performance measure.

Performance measure	Minimal-optimal number of candidate predictors	R^2 on holdout test set
Sprints	6	24.9%
HSR	7	42.0%
HMLd	6	48.4%
ACC	7	28.0%

Table 3. Predictors of sprint performance.

	Sprint Performance				
Predictors	*Estimates*	*ES*	*CI*	*Standardized CI*	*P*
(Intercept)	0.07		0.05 – 0.09		<0.001
Sprints AL	0.00	*Small* ↑	0.00 – 0.00	0.17 – 0.91	0.005
Sprints AL^2	-0.00	*Small*	-0.00 – -0.00	-0.94 – -0.22	0.002
Random Effects					
σ^2	0.00				
$\tau_{00\ Player\_ID}$	0.00				
ICC	0.43				
N_{Player_ID}	14				
Observations	270				
Marginal R^2	0.025				
Conditional R^2	0.447				

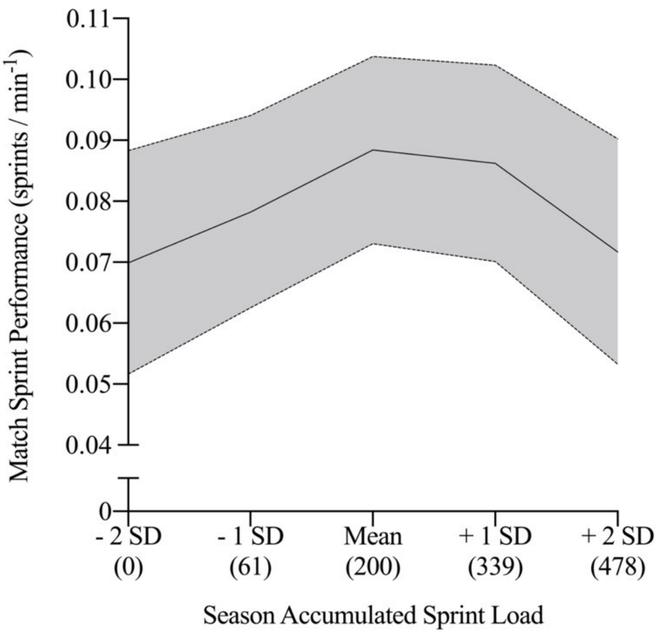

Figure 2. Quadratic relationship (P = 0.002; ES = *Small*) between season sprint accumulated load and match play sprint performance. Data are presented as mean ± 95% CI bands.

Table 4. Predictors of HMLd Performance.

	HMLd Performance				
Predictors	*Estimates*	*ES*	*CI*	*Standardized CI*	*P*
(Intercept)	24.00		18.75 – 29.25		<0.001
Wide Midfielders	5.16	*Small* ↑	1.91 – 8.40	0.18 – 0.79	0.008
Central Midfielders	2.40	*Small* ↑	-0.48 – 5.29	-0.06 – 0.70	0.133
Forwards	2.79	*Small* ↑	-0.99 – 6.58	-0.07 – 0.48	0.176
Wide Defenders	2.75	*Small* ↑	-0.58 – 6.07	-0.07 – 0.76	0.134
EWMA HMLd Acute	-0.02	*Moderate* ↓	-0.04 – -0.01	-1.24 – -0.16	0.012
EWMA HMLd Acute^2	0.00	*Moderate*	0.00 – 0.00	0.15 – 1.22	0.012
EWMA RPE Chronic	-0.02	*Trivial* ↓	-0.03 – -0.00	-0.36 – -0.01	0.042
EWMA HMLd Chronic	0.01	*Small* ↑	0.00 – 0.02	0.13 – 0.50	0.001
Random Effects					
σ^2	3.40				
$\tau_{00\ Player\_ID}$	4.48				
ICC	0.57				
N_{Player_ID}	18				
Observations	258				
Marginal R^2 /	0.399				
Conditional R^2	0.741				

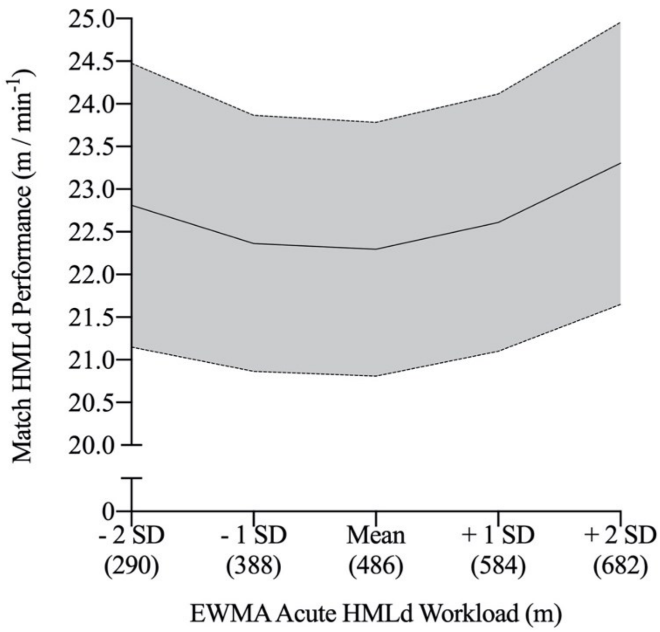

Figure 3. Quadratic relationship (P = 0.012; ES = *Moderate*) between acute High Metabolic Load Distance workload and match play High Metabolic Load Distance performance. Data presented as mean ± 95% CI bands.

Table 5. Predictors of HSR Performance

	HSR Performance				
Predictors	*Estimates*	*ES*	*CI*	*Standardized CI*	*p*
(Intercept)	2.80		1.11 – 4.49		0.003
Central Midfielders	1.23	*Small* ↑	-0.26 – 2.73	-0.06 – 0.61	0.146
Forwards	2.74	*Small* ↑	0.15 – 5.34	0.01 – 0.44	0.068
Wide Defenders	2.19	*Small* ↑	0.49 – 3.90	0.10 – 0.84	0.037
Wide Midfielders	6.36	*Small* ↑	3.52 – 9.20	0.19 – 0.51	0.001
HSR AL	0.00	*Moderate* ↑	0.00 – 0.00	0.28 – 0.92	<0.001
HSR^2 AL	-0.00	*Small*	-0.00 – -0.00	-0.82 – -0.19	0.002
EWMA chronic ACC+DEC	0.04	*Small* ↑	0.01 – 0.06	0.05 – 0.35	0.008
EWMA acute HMLd	-0.00	*Trivial* ↓	-0.00 – 0.00	-0.16 – 0.08	0.550
Random Effects					
σ^2	1.79				
$\tau_{00\ Player\_ID}$	1.14				
ICC	0.39				
N_{Player_ID}	14				
Observations	221				
Marginal R^2 / Conditional R^2	0.387 / 0.625				

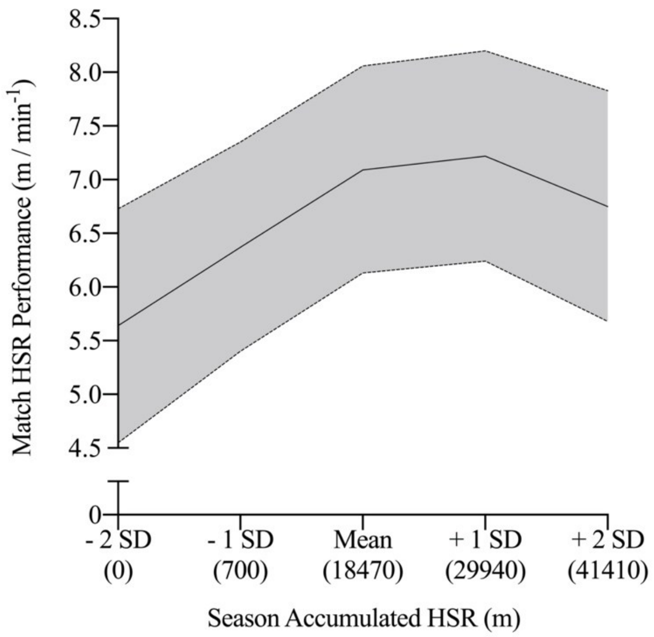

Figure 4. Quadratic relationship (*P* = 0.002, ES = *Small*) between season accumulated high-speed running workload and match play sprint performance. Data presented as mean ± 95% CI bands.

Table 6. Predictors of ACC Performance.

			ACC Performance		
Predictors	*Estimates*	*ES*	*CI*	*Standardized CI*	*p*
(Intercept)	1.06		0.96 – 1.17		<0.001
EWMA acute sprints	0.13	*Small* ↑	-0.01 – 0.26	-0.04 – 0.88	0.074
EWMA acute sprints^2	-0.04	*Small*	-0.09 – -0.00	-0.78 – -0.02	0.042
EWMA A:C sprints	-0.20	*Small* ↓	-0.42 – 0.02	-0.78 – 0.05	0.083
EWMA A:C sprints^2	0.15	*Small*	0.05 – 0.25	0.20 – 0.94	0.003
Goal Deficit	-0.01	*Trivial* ↓	-0.02 – -0.00	-0.21 – -0.04	0.004
Random Effects					
σ^2	0.02				
τ_{00} Player_ID	0.02				
ICC	0.54				
N Player_ID	18				
Observations	258				
Marginal R^2 / Conditional R^2	0.068 / 0.568				

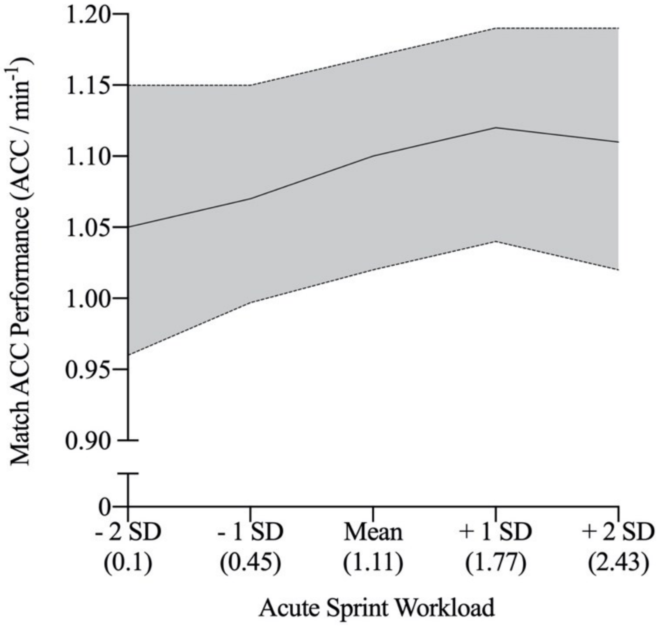

Figure 5. Quadratic relationship (*P* = 0.043; ES = *Small*) between acute sprint workload and match play acceleration performance. Data presented as mean ± 95% CI bands.

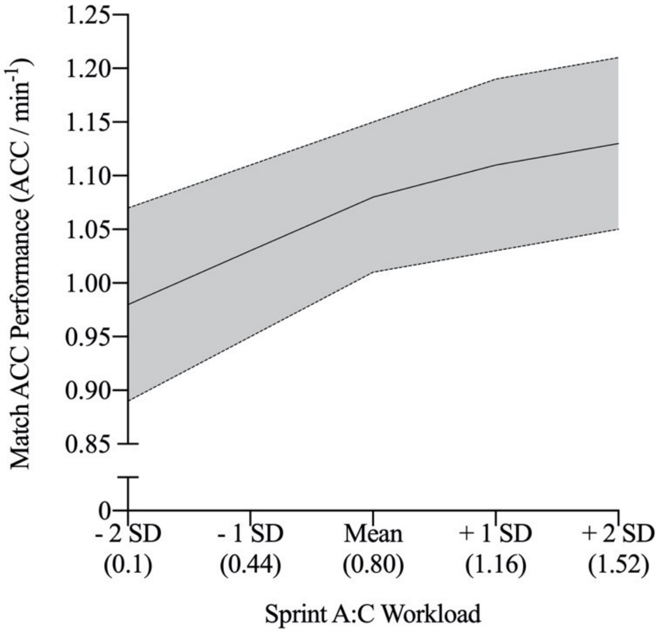

Figure 6. Quadratic relationship (*P* = 0.003; ES = *Small*) between sprint A:C workload and match play acceleration performance. Data presented as mean ± 95% CI bands.